Short title: Evaluation of Narrowband and Broadband Vegetation Indices for Determining Optimal Hyperspectral Wavebands for Agricultural Crop Characterization

One sentence description: Narrowband and broadband vegetation indices are evaluated to determine spectral bands and their bandwidths that provide optimal agricultural crop information.

The authors are: **Dr. Prasad S. Thenkabail** and **Dr. Ronald B. Smith** of Center for Earth Observation (CEO), Yale University, P.O. Box 208109, New Haven, Connecticut 06511, USA. e-mail: prasad.thenkabail@yale.edu ; Ronald.smith@yale.edu; and **Dr. Eddy de Pauw** of International Center for Agriculture in the Dry Areas (ICARDA).

Please address all correspondence to:

Dr. Prasad S. Thenkabail, Center for Earth Observation (CEO), Department of Geology and Geophysics, Kline Geology laboratory, P.O. Box 208109, 210 Whitney Avenue, Yale University, New Haven, Connecticut 06520-8109, USA. Fax: 203-432-3134, Tel.: 203-432-3440, e-mail: prasad.thenkabail@yale.edu

Evaluation of Narrowband and Broadband Vegetation Indices for Determining Optimal Hyperspectral Wavebands for Agricultural Crop Characterization

ABSTRACT

The main goal of the study was to determine optimal waveband centers and widths required to best estimate agricultural crop characteristics. The hyperspectral narrowband data was acquired over 395-1010 nanometer using a 1.43 nanometer wide, 430 bands, and hand-held spectroradiometer. Broadband data was derived using a Landsat-5 Thematic Mapper image acquired to correspond with field spectroradiometer and ground truth measurements. Spectral and biophysical data were obtained from 196 sample locations, including farms and rangelands. Six representative crops grown during the main cropping season were selected: Barley, wheat, lentil, cumin, chickpea, and vetch. Biophysical variables consisted of leaf area index, wet biomass, dry biomass, plant height, plant nitrogen, and canopy cover.

Narrowband and broadband vegetation indices were computed and their relationship with quantitative crop characteristics established and compared. The simple narrowband two-band vegetation indices (TBVI) and the optimum multiple band vegetation indices (OMBVI) models provided the best results. Compared to best broadband TM indices, TBVI explained up to 24 percent greater variability and OMBVI explained up to 27 percent greater variability, in estimating different crop variables. A Predominant proportion of crop characteristics are best estimated using data from 4 narrowbands, in order of importance, centered around: 675 nanometers (red absorption maxima), 905 nm (near infrared reflection peak), 720 nm (a portion of the red-edge), and 550 nm (green reflectance maxima). The study determined 12 spectral bands and their bandwidths that provide optimal agricultural crop characteristics, in the visible and near infrared portion of the spectrum.

Introduction and Background

Till recently, Earth Observation Satellites carried only broad-waveband sensors such as Landsat Enhanced Thematic Mapper (ETM+), Thematic Mapper (TM), Multispectral scanner (MSS), Le Syste′me pour l’observation de la terre (SPOT) high resolution visible (HRV), and the Indian Remote Sensing (IRS) Linear Imaging Self-Scanning (LISS). These sensors have known limitations in providing adequate information on terrestrial ecosystem characteristics such as in providing accurate estimates of biophysical and yield characteristics of agricultural crops (e.g., Asner et al., 2000; Carter, 1997; Gong et al., 1995; Richardson et al., 1992; Shaw et al., 1998; Thenkabail et al., 1995; Weigand et al., 1992), crop moisture variations (Peñuelas et al., 1995), leaf pigment concentrations (Blackburn and Steele, 1999), sensitivity to chlorophyll levels (Blackburn, 1999 and 1998), crop type or species identification (Asner et al., 2000), characterizing natural vegetation (Friedl et al., 1994; Goetz et al., 1985; Thenkabail, 1999), assessing crop or vegetation stress (Blackburn, 1998; Dawson and Curran, 1998), highlighting nitrogen or organic matter deficiencies (McGwire et al., 2000), detection of crop phenology (Badhwar and Henderson, 1981), land cover characterization (Thenkabail et. al., 2000a; Lyon et al., 1998), soil background effects (Elvidge and Chen, 1995), and in assessment of carbon fluxes (Fassnacht et al., 1997). Limitations such as these have lead to an increasing interest in the narrow-waveband sensors, which are expected to provide more detailed information and/or enable a host of new applications. The recent successful launches of Terra the Earth Observing System (EOS) flagship satellite and the Earth Observing-1 (EO-1) usher a new era of hyperspectral observations of the Earth from the Space. EO-1 carries the Hyperion sensor with 220 narrowbands each of 10 nm wide. Terra satellite has Moderate Resolution Imaging Spectrometer (MODIS) sensor with 36 wavebands, and Advanced Space borne Thermal Emission Reflectance Radiometer (ASTER) sensor with 15 wavebands. Upcoming hyperspectral sensor launches also include 105 narrow wavebands in the Australian Resource Information and Environment Satellite (ARIES) and Warfighter-1 with 200 narrow wavebands in a sensor onboard United States private industry satellite Orbview-4. All these sensors cover the 400 to 2500 nanometer spectral range. In the past, there has been significant experience in the use of near-continuous spectra from imaging spectrometers such as the NASA designed Airborne Visible-infrared Imaging Spectrometer (AVIRIS) and Compact Airborne Spectrographic Imager (CASI). However, hyperspectral data from satellites is new to users, just as Landsat data was new in 1972 when Earth Resources Technology Satellite (ERTS later renamed Landsat-1) was launched. It is expected that data from the hyperspectral sensors will open a new phase in terrestrial application (e.g., Clark et al. 1998). Nevertheless, a complex set of issues needs to be resolved when handling hyperspectral data that include (Gat, 1995) data storage volume, data storage rate, downlink or transmission bandwidth, real-time analog to digital bandwidth and resolution, computing bottle neck in data analysis, and new algorithms for data utilization. The Hyperion and other Hyperspectral sensors will produce very large data volumes, which make it imperative that newer methods and techniques be developed to handle these high-dimensional datasets.

Even better will be to focus on design of an optimal sensor for a given application by dropping redundant bands. Optimal hyperspectral sensors will help reduce data volumes, eliminate the problems of high-dimensionality of Hyperspectral datasets, and make it feasible to apply traditional classification methods on a few selected bands (optimal bands) that capture most of the information of crop characteristics. Future generations of satellites are either likely to carry specialized optimal sensors focussed to gather data for targeted applications, or carry a narrow-waveband hyperspectral sensor like Hyperion from which users with different application needs can extract appropriate optimal wavebands. Thereby, knowledge of application specific "optimal bands" for high dimensional datasets such as Hyperion and Warfighter-1 is mandatory to reduce costs in data analysis and computer resources. Table 1 compares the spectral and spatial resolution of narrowband, and broadband data used in this study with the characteristics of well known narrowband AVIRIS airborne and recently launched Hyperion space borne sensors.

A number of recent studies have indicated the advantages of using discrete narrowband data from specific portion of the spectrum when compared with broadband data to arrive at optimal quantitative or qualitative information on crop or vegetation characteristics (e.g., Nolin and Dozier, 2000). For example, the optimal individual wavebands for pigment estimation are identified empirically as 680 nm for chlorophyll a, 635 nm for chlorophyll b and 470 nm for the carotenoids (Blackburn, 1999). Measurements on bracken (Pteridium aquilinum) showed that both Chlorophyll a and Chlorophyll b concentrations were most strongly correlated with 676 nm (Blackburn, 1998). In the same study, during senescence Chlorophyll a was best correlated with 680 nm and carotenoids was best correlated with 470 nm. Hyperspectral data has shown the promise of providing significant additional information in estimates of crop biophysical characteristics compared to similar information obtained from broadband sensors (Blackburn, 1998; Carter, 1998; Elvidge and Chen, 1995; Thenkabail et al., 2000b and 1999). The results were based on studies conducted using data gathered from field spectroradiometers (Carter, 1998; Elvidge and Chen, 1995, Thenkabail, et al. 2000b), CASI (e.g., Jacobsen et al., 2000; Gong et al., 1995), and AVIRIS (e.g., Sanderson et al., 1998). These studies were conducted for rice yield (Shibayama and Akiyama, 1991), crop or vegetation characteristics (Elvidge and Chen, 1995; Thenkabail, et al. 2000b), chlorophyll content of slash pine (Curran, 1990), coniferous forest LAI (Gong et al., 1995), pinyon pine canopy LAI (Elvidge and Chen, 1995), and photosynthesis and stomatal conductance in pine canopies (Carter, 1998). Asner et al. (2000) demonstrated the ability of hyperspectral data to delineate distinct features of foliage, litter, wood, and soil, that would result in more accurate quantitative biophysical assessments compared to broadbands. Carter (1994) showed that the ratios that most strongly indicated plant stress were reflectance at 695 nm divided by reflectance at 420 nm or 760 nm. Studying the spectral reflectance of senescing leaves of two deciduous species (maple and chestnut) as well as their pigment content Gitelson and Merzlyak (1996) found that the maximum sensitivity of reflectance coincides with the maximum absorption of chlorophyll a at 670 nm. They concluded that the maximum sensitivity to chlorophyll a concentration was found at 550-560 nm and 700-710 nm and reflectance's at 700 nm correlated very well with that at 550 nm for a wide range of chlorophyll concentrations for both plant species studied. Thenkabail et al. (2000b and 1999) highlighted the advantages of using narrowband data at specific portions of the spectrum when compared with broadband data in studying agricultural crop characteristics. Elvidge and Chen (1995) minimized the soil background effects using derivative based vegetation indices, which measure the amplitude of the chlorophyll red-edge using continuous narrow-band spectra from 626 nm to 795 nm. Wavebands centered at 575 nm and 520 nm are found to be sensitive to pigment content and chloroplast changes (Nichol et al., 2000), whereas wavebands centered at 470 and 800 nm were found useful in structure insensitive pigment index (SIPI) by Peñuelas et al. (1995). Total chlorophyll was very highly correlated with a ratio involving 550 nm and 850 nm for corn (Zea mays L.) crop (Schepers et al., 1996). Aoki et al. (1981) proposed the ratio between two narrowbands at 500 nm and 850 nm as a nondestructive method for estimating leaf chlorophyll concentration. Similarly, Gitelson and Merzlyak (1996) found that a "green NDVI," employing a green band centered on 500 nm rather than a red band as in the traditional NDVI, was highly correlated with Chlorophyll a concentrations of maple and chestnut leaves and sensitive over the range 3-450 mg m^2. Indices derived from wavebands centered at red edge portion (703nm, 722nm, and 730nm) along with wavebands in the beginning of red-edge (700 nm) and end of red-edge (757 nm) were found to be strongly correlated with cover and biomass of Scots pine (Pinus sylvestris L.) (Shaw et al., 1998). Red-edge is strongly correlated with foliar chlorophyll content and is a very sensitive indicator of vegetation stress (Dawson and Curran, 1998). The red-edge region centered at 717 nm is particularly important for extracting additional information about chlorophyll and nitrogen status of plants (Clevers, 1999). Thenkabail et al. (2000b and

1999), based on a study of 5 crops in semi arid and arid environments, showed that only 12 of the 512 narrow-bands could provide optimal crop biophysical information.

The Main goal of this paper was to determine optimal hyperspectral narrow wavebands, in the visible and near-infrared portion of the spectrum, that best characterize agricultural crop characteristics. Vegetation indices derived from narrow and broad wavebands were used to establish relationships with crop biophysical variables and yield. Data were acquired from 176 farmer or researcher managed farms and 20 marginal land (or rangeland) plots in the arid and semi-arid environments of Syria using: (a) narrow waveband data from 1.43 nanometer wide 512 discrete narrowbands in the visible and NIR portion (350 to 1050 nanometers) of the spectrum, and (b) broad waveband data from the 6 non-thermal bands (450 to 2350 nm) of Landsat-5 TM sensor. The study was conducted during April-May, 1998 during the main (spring) cropping season.

Study Area

The study area is located around Aleppo, Syria in the desert-margins of Southwest Asia where agriculture faces complex challenges due to inadequate rainfall. The long term mean rainfall during the effective growing season of November-May is 373 mm. Approximately 50 percent of the work force earns its living directly from agriculture, placing great stress on the sustainability of land and water resources. Worldwide an estimated one billion people currently live in countries and regions included in the desert-margins with the population growth rates of 2.1 percent in the Central Asian Republics and 3.6 percent in the Mediterranean regions. The bounding coordinates of the study area are in Syria: upper left: 36.30N, 36.50E; upper right: 36.30N, 37.43E; lower right: 35.56N, 37.43E; and lower left: 35.56N, 36.50E. The study area consists of researcher managed and farmer managed farms growing mainly cereals (wheat, barley), and legumes (vetch, lentil, chickpea) intermingled with cumin, fallow farms and rangelands in the main crop-growing season. Figure 1 shows these characteristics in a portion of the study area.

Methods and Procedures

Narrowband, broadband, and ground truth data were extracted from 196 specific locations spread across the study area in farmer and researcher managed farms and marginal lands. Sample sites were located using a Garmin^{TM} Geographic Position Systems (GPS) and consisted of barley (44 sample locations), wheat (64), lentil (23), cumin (17), chickpea (14), vetch (14), marginal lands (20) and fallow farms or top soils (9) (see representative samples in Figure 2).

Hyperspectral data

Narrowband data was gathered to coincide with broadband Landsat-5 TM acquisition. Narrowband data was acquired during April 13 through May 5, 1998 using a hand-held spectroradiometer manufactured by Analytical Spectral Devices^{TM} providing data in 1.43 nm wide 512 discrete narrowbands in the visible and near infrared (332-1064 nm). Spectroradiometer unit consists of a main spectrometer, a personal computer, fiber optic cable, a pistol grip, and different field of view (FOV) cones. Inside the spectrometer instrument, light is projected from the fiber optics onto a holographic diffraction grating where wavelength components are separated and reflected for independent collection by the detector(s) (FieldSpec, 1997). Each detector converts incident photons into electrons that are stored, or integrated, until the detector is read out. At the read out time, the photoelectric current for each detector is converted to a voltage and is digitized by a 16-bit analog to digital (A/D) converter. This data is directly transferred to the computer main memory, which is in turn available for further processing, by the controlling software (FieldSpec, 1997). Gathering spectra at any given location involved optimizing the integration time (typically set at 17 milliseconds), providing foreoptic information, recording dark current, collecting white reference reflectance, and then obtaining target reflectance. The target reflectance is the ratio of energy reflected off the target to energy incident on the target (measured using a $BASO_4$ white reference). Since the dark current varies with time and temperature it was gathered for each integration time (virtually for each new set of readings along a transect in a sample site location). Due to severe noise in data in the long and short ends of the spectrum, only the data gathered in 395 nm through 1010 nm was used in the study reducing the number of spectral channels to 430.

Reflectance=((target-dark current)/(reference-dark current))*100 percent.

Spectral data from Spectroradiometer and quantitative and qualitative data on crops, and on soils were obtained from 196 ground truth locations spread across the study area- Measurements were made with nadir looking 18-degree field of view (FOV). All canopy-level measurements were acquired at a height of approximately 1.20 m above the ground, with a 38 cm diameter footprint on the ground, resulting in an area of 1134 cm^2 observed on ground. Each acquired spectra was an average of 10 individual measurements that were automatically acquired by the FieldSpec. Ten to fifteen such measurements were made along a 30 meter transect at each ground truth location. All individual spectral responses for each field were plotted and visually examined to remove any significant outliers occurring as a result of poor acquisition conditions. All the remaining spectra along the transect were averaged to constitute a single representative spectra for the sample site location.

Narrowband reflectivity obtained at ground level is free of any atmospheric effects. The mean hyperspectral characteristics of 6 agricultural crops, rangelands, and fallows are plotted in Figure 3. The representative growth stages of crops are varied from late vegetative to critical in most cases (Figure 2).

Broadband data

Broadband data was extracted using Landsat-5 TM image of sixth April, 1998. Mean digital values for the 6 non-thermal bands were extracted from a 3 by 3 pixel area from each of the 196 sample site locations. The GPS location is centered on this 3 by 3 pixel area. Broadband data were also derived simulating discrete narrowband data of spectroradiometer (which is free from atmospheric effects since the data is acquired at ground level). Preliminary investigations showed the simulated broadband data provided significantly similar results as atmospherically corrected at satellite exatmospheric reflectance based Landsat-5 TM broadband data in their relationships with agricultural crop variables. Also, in a recent study Thenkabail et al. (2000) performed a detail comparison of the simulated broadband TM data with the narrowband data. Thereby, only the broadband data derived from Landsat-5 TM sensor has been reported throughout this paper and will simply be referred to as "broadband" data. The broadband data are corrected for atmospheric effects, and the digital numbers are converted to radiance and at satellite exatmospheric reflectance before being compared with narrowband data.

Correction for Atmospheric scattering

In arid and semi-arid regions most atmospheric effect are due to scattering of light by gas molecules and aerosols. Landsat-5 TM data was corrected for atmospheric scattering effects using Milton spreadsheet (Milton, 1994) based on Chavez modified dark-object subtraction technique (Chavez, 1988; and 1989). Since the image was very clear, a Rayleigh relative scattering model of $\lambda^{-4.0}$ was used. Scene-based atmospheric scattering correction procedures are based on the observation that the degree of scattering is strongly wavelength-dependent: it affects blue wavelengths much more than red and infrared wavelengths. Chavez procedure involves selection of a starting haze value (SHV) for band 1 or band 2 and determining the haze-equivalent DN value for each band. For April 6, 1998 Landsat-5 TM the SHV of band 1 was 50 (determined by plotting a histogram of band 1). The haze DN values for band 2-5 and 7 were, 10, 6, 0, 0, and 0 respectively. The SHV and haze DN values were deducted from each band to obtain an atmospheric scattering corrected image.

Digital number to radiance and at-satellite exatmospheric reflectance

Broadband digital counts are converted to at-satellite exatmospheric reflectance's using the following procedure. Mean Landsat-5 TM digital numbers from 3 by 3 pixel locations were first converted to Spectral radiance (Price, 1987) using the equation:

$R_i = \alpha_i \, DN_i + \beta_i$ ……….(1)

where, R_i = spectral radiance in mW $cm^{-2}sr^{-1}\mu m^{-1}$; α_i = gain or slope in mW $cm^{-2}sr^{-1}\mu m^{-1}$; β_i = bias or intercept in mW $cm^{-2}sr^{-1}\mu m^{-1}$; DN_i = digital number of each pixel or mean of a number of pixels in TM bands where i = 1 to 5 and 7 (except the thermal band 6). The α_i and β_i are calculated using the post calibration maximum (L_{max}) and minimum (L_{min}) radiance values provided in the header file of EOSAT fast format tapes where α_i = gain = (maximum radiance/254)- (minimum radiance/255, and β_i = bias = minimum radiance. L_{max} values (in mW $cm^{-2}sr^{-1}$) for April 6, 1998 images were: 1.059476, 2.611919, 1.639662, 2.949823, 0.683888, and 1.52431. L_{min} (in mW $cm^{-2}sr^{-1}$) values were: -0.016946, -0.041805, -0.026226, -0.059251, -0.016548, and 0.12378.

The above calculations for α_i and β_i result in spectral radiance values in mW $cm^{-2}sr^{-1}$ for each farm or set of pixels within each farm. These values are then divided by the respective bandwidths to obtain spectral radiance units in mW $cm^{-2}sr^{-1}\mu m^{-1}$. The Landsat-5 TM bandwidths (in μm) are: TM1: 0.066, TM2: 0.082, TM3: 0.067, TM4: 0.128, TM5: 0.217, TM6: 1.000, TM7: 0.252. This helps normalize the effects of bandwidths in spectral data. The above calculations lead to R_i values in milliwatts/ (square centimeter-steradian-micrometer) expressed as mW $cm^{-2}sr^{-1}\mu m^{-1}$.

The effective at-satellite apparent reflectance (ρ_p-unitless) is calculated using spectral radiance (R_i), earth-sun distance (d) expressed in astronomical units (A_u), solar zenith angle (θ) (which is 90 degrees minus the sun elevation or sun angle when the scene was recorded as given in the image header file), and solar flux or exatmospheric irradiances (F_0) (Markam and Barker, 1985; 1987). This provides the nadir reflectance from both the surface and the atmosphere above it and normalizes the effects of solar elevation, and earth-sun distance. This is also referred to in literature variously as planetary albedo or exatmospheric reflectance. F_0 (mW cm^{-2} sr^{-1} μm^{-1}) is obtained from Nickel and Labs (1981 and 1984) and for TM bands were: TM1: 194.648, TM2: 181.263, TM3: 154.595, TM4: 104.67, TM5: 21.112, TM6: 1, and TM7: 7.691. The value of d (unitless) varies between 0.96 to 1.04, can be obtained from nautical handbook (see Markham and Barker, 1987), but is often assumed as 1. The solar elevation for the April 5, 1998 image was 51 degrees (from EOSAT header file) and hence θ will be 39 degrees.

$$\text{at-satellite or apparent reflectance } (\rho_p) = \frac{\pi R_i d^2}{\cos(\theta) * F_0} \rightarrow (2)$$

Broadband vegetation indices are computed using at-satellite exatmospheric reflectances.

Ground-truth data

At each of the 196 locations ground data collected included: GPS locations, crop samples to obtain quantitative characteristics such as LAI and biomass, observations of plant conditions and growth stages, canopy cover, digital photographs, and slide photographs. Sample locations were chosen randomly by driving around the study area and stopping for measurements at various locations. At each farm, an area of 30 m by 30 m that was considered representative portion of the farm was chosen for all measurements. Six main crops that occupy most of the cultivated area were identified for spectral and crop biophysical measurements. The spring (November-May) is the main cropping season in the study area. The ground truth data were collected during April-

May 1998 when most crops were in critical, or tillering or late vegetative growth phases. The major crops were (Figure 3): Barley (*Hordeum vulgare L.*; sample size 44), wheat (*Triticum aestivum L. or Triticum durum Desf.*; 64), lentil (*Lens esculenta Moench. Or Lens orientale (Boiss.) Schmalh. Or Lens culinaris Medikus*; 23), cumin (*Cuminum cyminum L.*; 17), chickpea (*Cicer arietinum L.*; 14), and vetch (*Vicia narbonensis L.*; 14). Measurements were also taken from marginal lands (20) and fallow farms or top soils (9).

Above ground plant samples within a 34 cm by 34 cm (1156 cm^2) block were taken for Laboratory analysis. In the laboratory, plant samples were analyzed for leaf area (m^2), wet weight (kilograms), dry weight (kilograms), and plant Nitrogen content (percent). Leaf area was obtained by running the leaves over a LI-COR 3100 leaf area meter. The leaf area (cm^2) obtained from plants in representative area of 1156 cm^2 of farm is converted into leaf area index (m^2/m^2). Plants were cut and weighed on a simple weighing machine to get weight per 1156 cm^2. This weight was converted into biomass (kg/m^2). Crop yield was obtained only for selected wheat farms through after harvest actual yield measurements (tonnes per hectare). Above ground plant height (PLNTHT) was measured directly in the field. Each plant sample was dried in oven at 70°C, dry weights measured and converted into dry biomass (kg/ m^2). The dried plants were crushed and assessed for plant crued protein (percentage) and Nirogen (percentage) for all crops and marginal lands. The mean nitrogen content (in percent) was: Vetch 3.24, lentil 2.7, wheat 1.66, barley 1.17, chickpea 3.01, cumin 3.13, and marginal lands 1.45. The mean canopy cover (also in percent) was: vetch 88, lentil 90, wheat 97, barley 97, chickpea 69, cumin 48, and marginal lands 68.

Hyperspectral and multispectral vegetation indices

There is no single best approach to determine the optimal number of narrow wavebands required to provide best estimates of agricultural crop characteristics. In the past, researchers have used reflectance from individual narrowbands (Mariotti et al., 1996), various ratio indices (Aoki, 1981;

Carter, 1994; Lichtenthaler et al., 1996), derivatives of reflectance spectra (Elvide and Chen, 1995; Curran et al. 1991), or a combinations of these (Thenkabail et al., 1999), principal component analysis (Asner et al. 2000; Clevers, 1999; Thenkabail, 2001), discriminant analysis (Vaesen et al., 2001; Thenkabail, 2001), and linear mixture modeling approach (Elmore et al., 2000; Mass, 2000). The main focus in this paper will be to conduct a rigorous evaluation of narrowband versions of (a) Two band vegetation indices (TBVI) and (b) Optimum multiple band vegetation indices (OMBVI) in establishing relationships with agricultural crop growth and yield characteristics. Broadband versions of TBVI and OMBVI as well as 6 other broadband indices and their narrowband versions are computed, discussed, and compared with TBVI and OMBVI.

1. Two band vegetation indices (TBVI) (Thenkabail et al. 2000b; this paper)

The TBVI for narrow-bands i and j will be:

$$\text{narrow-band TBVI}_{ij} = \frac{(R_j - R_i)}{(R_j + R_i)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (1)$$

where, i,j = 1, N, with N=number of narrow-bands=430 (each band of 1.43-nm-wide spread over 395 nm to 1010 nm), R=reflectance of narrow-bands. All computations were performed by writing simple NDVI algorithms for all possible combinations of 2 band indices using Statistical Analysis System (SAS, 1997).

Broadband versions of TBVI were computed from equation 1 using data from 6 non-thermal Landsat-5 TM bands. Broadband data can also be derived by aggregating discrete narrowband data over required bandwidths. Using that procedure, Thenkabail et al. (1999) established that the vegetation indices computed for currently existing satellite sensors (e.g., Landsat MSS, Landsat TM, SPOT HRV, and IRS-1C) were highly correlated (R^2 value=0.95 or higher) and hence computing vegetation index for any one of these broadband sensors will suffice. Thereby, results obtained for broadband TBVI should be relevant for a of wide range of other sensors.

The narrowband and broadband TBVI's were then related to crop biophysical variables using the SAS (SAS, 1997). Linear or non-linear models were fitted based on the plot trends and best-fit R^2 values. When non-linearity existed , exponential or power or quadratic models were fitted. These equation forms were exponential (crop variable=$a*e^{b*VI}$), quadratic ($a*VI^2+b*VI+c$), linear (a+b*VI), and power ($a*VI^b$); where a=slope and b=intercept of soil line (obtained by plotting RED versus NIR bands), and VI= vegetation index. Non-linear exponential relationships provided the best fits in most relationships and were hence adopted.

2. Optimum multiple band vegetation indices (OMBVI) (Thenkabail et al., 2000b; this paper)

The narrowband and broadband versions of OMBVI were computed using the following model equation:

$$OMBVI_i = \sum_{J=1}^{N} a_{ij} R_j \text{ .... (2)}$$

where, OMBVI = crop variable i, R = reflectance in bands j (j= 1 to N with N=430); a = the coefficient for reflectance in band j for i th variable.

Of several statistical methods available to run piecewise linear regression models, the stepwise MAXR procedure is considered the best (SAS, 1997) and hence used in this study. The MAXR method begins by finding the variable (R_j) producing the highest coefficient of determination (R^2) value (SAS, 1997). Then another variable, the one that yields the greatest increase in R^2 value, is added. Once the two-variable model is obtained, each of the variables in the model are compared to each variable not in the model. For each comparison, MAXR determines if removing one variable and replacing it with the other variable increases R^2. After comparing all possible choices, the one that produces the largest increase in R^2 is made. Comparisons begin again, and the process continues until MAXR finds that no replacement could increase R^2. The two-variable model thus achieved is considered the best two-variable model. Another variable is then added to the model, and the comparing-and-switching process is repeated to find the best three-variable model, and so forth (SAS, 1997) until the best n-variable model is determined.

3. NIR and RED based normalized difference vegetation Indices (NDVI) (Rouse et al., 1973; Jackson, 1983)

$$\text{NDVI} = \frac{(\text{NIR-red})}{(\text{NIR+red})} \quad \text{................................} \quad (3)$$

Where,

For broad-bands (Landsat-5 TM): RED (TM3): 630-690 nanometers, NIR (TM4): 760-900 nm

For narrow-bands (hyperspectral): RED (λ_1=675 nm): 668-683 nanometers ($\Delta\lambda_1$ = 15 nm), NIR (λ_2=905 nm): 898-913 nm ($\Delta\lambda_2$ = 15 nm); where λ_1=is band center; and $\Delta\lambda_1$ = is bandwidth.

4. Transformed soil adjusted vegetation indices (TSAVI) (Baret et al., 1989)

$$\text{TSAVI} = \frac{a*(\text{NIR}-a*\text{red}-b)}{(\text{red}+a*\text{NIR}-a*b)} \quad \text{............................} \quad (4)$$

where, a=slope an b=intercept of soil lines. Forty-three spectral measurements of soils were taken using the Spectroradiometer at the topsoil. The distinct soil types in the study area were (see Ryan, 1997): very fine clayey *Calcixerollic Xerochrept and Chromic Calcixerert* (in Tel Hadya region), very fine clayey *Chromic Calcixerert* (Jindiress), and *clayey Calcixerollic Xerochrept* (Breda). The slopes (a) and intercepts (b) of the soil lines were computed by plotting mean reflectances for broadbands and narrowbands using RED and NIR bandwidths as provided for equation 3 above. These are fitted using the equation: NIR=a* RED + b.

5. Atmospheric corrected vegetation indices (ACVI) (Kaufman and Tanre, 1994)

$$\text{ACVI} = \frac{(\text{NIR-rb})}{(\text{NIR+rb})} \quad \text{...........................} \ (5)$$

<u>Where,</u>

rb = RED - gamma * (RED-BLUE); gamma = 1, BLUE = TM1.

It was not necessary to compute ACVI for narrowbands since atmospheric effects were not significant for hyperspectral measurements made at ground level.

6. Middle infrared-based vegetation indices (MIVI) (Thenkabail et al., 1995)

$$\text{MIVI} = \frac{(\text{ MIR1-RED})}{(\text{MIR1+RED})} \quad \text{.................................} \ (6)$$

<u>Where,</u>

MIR1 (TM5): 1550-1750 nm . The hyperspectral observations were only in visible and NIR and hence MIVI was computed only for broadbands.

7. Tassel cap based greenness vegetation indices (TCGVI) (Jackson, 1983)

The Gram-Schmidt process (Jackson, 1983) was used to compute n-dimensional indices. The second component will provide TCGVI. Tassel cap equations were computed using 6 non-thermal bands of Landsat-5 TM image of April 05, 1998 covering the study area. TCGVI was not computed for narrowbands since it was beyond the scope of this paper.

Wetness (first component)

TM1*0.2909-TM2*0.2728+TM3*0.1446+TM4*0.8461+TM5*0.0549+TM7*0.1706

Greenness (GVI) (second component)

TCGVI = -TM1*0.2728-TM2*0.2174-TM3*0.5508+TM4*0.7221+TM5*0.0733-TM7*0.1648 .... (7)

Brightness (third component)

TM1*0.1446+TM2*0.1761+TM3*0.3322+TM4*0.3396-TM5*0.6210-TM7*0.4186

8. Principal component vegetation indices (PCVI) (this paper)

Principal components analysis (Jensen, 1986) was used to reduce many bands of broadband and narrowband data to few bands. Typically, the first 2 components explained about 90 percent of all variability in data (see Thenkabail, 2001). Using the weightings of the first principal component, new principal component band 1 brightness values (PCA1BV) are calculated. Similarly, using the weightings of the second principal component, new principal component band 2 brightness values (PCA2BV) are calculated. For example: digital numbers of 6 TM bands for field number 112 (barley crop) were: 57, 24, 24, 73, 52, and 18. The PCA1 coefficients were:-0.0564, 0.42323, 0.4455, 0.44708, 0.45723, and 0.45857. Thereby, the new brightness value, PCA1BV, for barley field number 112 will be: 82.3019. Using the new principal component bands 1 and 2, a principal component vegetation index was computed:

$$\mathrm{PCVI} = \frac{(\mathrm{PCA1BV} - \mathrm{PCA2BV})}{(\mathrm{PCA1BV} + \mathrm{PCA2BV})} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Results and discussions

Spectral characteristics

Mean spectral plots of 6 agricultural crops, marginal lands and soils illustrate several unique plant characteristics at specific portions of the spectrum (see Figure 3a through 3d). The erectophile (about 65 degrees) structure of two cereal crop (wheat and barley) canopies contribute significantly to steep slope in the near infrared (NIR) spectra in 740-940 nanometers range (Figure 3a). Reflectivity in the visible spectrum range of 450-700 nm is dramatically different for wheat when compared with barley (Figure 3a). This is due to growth stage differences with critical growth phases for wheat (Figure 2b) compared to senescing barley (Figure 2b). Wheat is greener compared to a mixture of brown and green in fast drying barley resulting in dramatically higher visible reflectance in barley. Two of the legumes, lentil and vetch, have very high NIR reflectance and very high red absorption (Figure 3b). There are number of reasons for this. Both lentil and vetch are in late vegetative vigorous growth phases with mean canopy cover was about 90 percent for both crops (Figure 2c and 2d). Both are nitrogen fixation crops with relatively high plant nitrogen content of 3.24 percent for vetch and 2.70 percent for lentil when the samples were taken. Compared to legumes, the plant nitrogen in wheat was 1.66 percent and barley 1.17 percent. Lentil, vetch, chickpea, and cumin are significantly shorter and more greener than wheat or barley. Soil background effects were significant for cumin with 48 percent canopy cover and chickpea with only 69 percent canopy cover (Figure 2e and 2f) resulting in relatively low NIR reflectance and high visible reflectance for these crops. Marginal lands are mixture of various levels of green, dry biomass. They also often have significant barren patches. These conditions result in steep NIR and visible reflectance slopes, a high degree of sensitivity in the red-edge (700 to 740 nm), higher reflectance in the visible and a very mild 'trough" in the 940-1010 nm moisture sensitive region (Figure 3d). In the 675 nm to 700 nm range, soil-crop contrast is significantly higher for healthy and vigorous crops (e.g., Figure 3b) when compared with crops or vegetation that are senescing (e.g., barley in Figure 3a) or with significant soil background effects (e.g., cumin or chickpea in Figure 2c) or with mix of dry and green vegetation conditions (e.g., rangelands in Figure 3d).

In the following section various indices are computed from the reflectance spectra. Broadband and narrowband versions of the best 2-band NDVI-type vegetation indices (TBVI) and optimum multiple band vegetation indices (OMBVI) were computed and compared with 6 other types of vegetation indices (NDVI, TSAVI, ACVI, MIVI, TCGVI, and PCVI).

Narrowband and broadband TBVI and crop variables

The relationships between narrowband and broadband TBVI with crop biophysical variables (wet biomass-WBM, dry biomass-DBM, leaf area index-LAI, and plant height-PLNTHT) were established and their coefficient of determination (R^2) determined for the 6 crops (Table 2). TBVI was also related to plant nitrogen and canopy cover, but these relationships were generally not as strong as with WBM, DBM, LAI, and PLNTHT. Hence, results with plant nitrogen and canopy cover will not be reported. Relationships were also established for wet and dry biomass of marginal lands (Table 2). A contour plot of the R^2 values for wavelength pairs λ_1 (395 to 1010 μm) and λ_2 (395 to 1010 μm) are plotted for: (a) LAI of barley (values below the diagonal in Figure 4), (b) LAI of wheat (values above the diagonal in Figure 4), (c) WBM of lentil (values below the diagonal in Figure 5), (d) WBM of chickpea (values above the diagonal in Figure 5). For a given crop variable, it will suffice to display the matrix only below (or above) the diagonal of the matrix as the R^2 (λ_1 and λ_2) values above and below the diagonal of the matrix are symmetrical. Only R^2 values above 0.4 are plotted for clarity. These plots show the waveband combinations that provide the best indices (see various "bulls-eye" formations in Figure 4 and 5) for relationships with crop biophysical variables. For example, waveband centers for the best TBVI index for barley LAI were 720 nm and 815 nm providing R^2 in the range of 0.76-0.79 (Figure 4) with the precise R^2 value of the best index as 0.79 (Table 2). Similarly, the best estimates of wheat LAI are obtained using two narrowbands centered at 680 nm and 910 nm (Figure 4) providing an R^2 value of 0.74 (Table 2). Lentil WBM was best estimated using 2 narrowbands centered at 675 nm and 910 nm explaining 85 percent variability (R^2 value of 0.85) whereas a TBVI derived using 568 nm and 678 nm explained 95 percent variability in chickpea WBM (Figure 5). Similar λ_1 versus λ_2 plots were used to determine the best waveband combinations estimating other biophysical variables of 6 crops and marginal lands (Table 2). Also computed were the best possible combinations of Landsat-5 TM broadband TBVI indices (Table 2). Narrowband TBVI indices consistently performed better than their broadband versions by explaining 1 to 24 percent greater variability (with a mean of about 10 percent) in determining various crop variables (Table 2). This improvement is probably due to a combination of greater dynamic range, more robustness to complex mix of growing conditions and growth stages, and greater sensitivity to plant pigmentation, canopy structure, and soil background effects. Generic relationships involving multiple crops that have a wide range of growing stages, growing conditions, and background effects are used to illustrate this. For example, NIR and red based broadband TBVI relationships with LAI and wet biomass of 6 crops (Figure 6a and 6b) show far less sensitivity or dynamic range or robustness when compared with NIR and red based narrowband TBVI with LAI and wet biomass of 6 crops (Figure 7a and 7b). These generic relationships are specifically useful in global change studies and macro-level crop simulation models.

In general, one or more narrowband indices provide greater dynamic range and are more robust in accounting for variability in a wide range of conditions such as soil background effects, growth stages, and pigmentation levels resulting in significantly improved R^2 values compared to best broadband Landsat-5 TM indices as illustrated for barley wet biomass (Figure 8a and 8b), wheat wet biomass (Figure 8c and 8d), wheat LAI (Figure 9a and 9b), and cumin LAI (Figure 9c and 9d). It needs to be noted that broadband data stretches from 450 nm to 2350 nm (non thermal TM bands) and include mid-infrared bands (TM5 and TM7) whereas the narrowband data was acquired only in 395-1010 nm. Thereby, the narrowband results are even more significant.

Optimal narrowband bandwidths were determined from the λ_1 versus λ_2 plots by observing the change in R^2 value from the band centers. For example, for barley LAI, along λ_1 the value of R^2 remains constant from about 750 nm to 880 nm with the center at 815 nm resulting in a $\Delta\lambda_1 = 130$ nm (Figure 4 and Table 3). However, along λ_2 the value of R^2 remains constant only for a very narrow width of about 10 nm ($\Delta\lambda_2$) with center at 720 nm (Figure 4). The bandwidths were rounded off to the nearest 5's or 10's (e.g., 8.5 nm is rounded off to 10 nm). For wheat LAI (Figure 4), both the λ_1 (680 nm) and λ_2 (910 nm) have a narrowband width of about 20 nm

($\Delta\lambda_1$=$\Delta\lambda_2$) with an R^2 value of 0.74. For lentil WBM, the best TBVI provided very narrowband widths of $\Delta\lambda_1 = \Delta\lambda_2$ = 20 nm for band centers λ_1 = 675 nm and λ_2 = 910 nm (Figure 5). Similarly, for chickpea WBM (Figure 5) the band centers and bandwidths were: λ_1 = 568 nm ($\Delta\lambda_1$=10 nm) and λ_2 = 678 nm ($\Delta\lambda_2$=10 nm). The bandwidths for LAI and biomass of all 6 crops and marginal lands were summarized in Table 3. The best NIR and red based narrowband indices can be computed by taking a: (a) very-narrowband centered around 675 nm ($\Delta\lambda$ = 15 nm) for red, and (b) narrow-band cantered around 905 nm or 920 nm ($\Delta\lambda$ = 15 nm) for NIR.

Optimum multiple band vegetation indices (OMBVI) and crop variables

Using the MAXR procedure of SAS (1997) the best 1-variable, 2-variable, and 3-variable OMBVI models were determined for estimating wet biomass, dry biomass, leaf area index, and plant height of 6 crops (Table 4). The best 1-variable narrowband model explained 38-94 percent of variability across different crop variables (Table 4). This increased to 56-98 percent for best 2-variable models and 60-99 percent for best 3-variable models. In overwhelming number of cases, further addition of independent variables only increased R^2 values insignificantly. Hence 3 bands are considered optimal. The addition of a third band often helps overcome the problem of saturation associated with 2 band NDVI type indices. However, the problem of "over fitting" (e.g., using more spectral channels than experimental samples to obtain a perfect R^2 value) needs to be avoided while using OMBVI models (See Blackburn, 1998; and Thenkabail et al., 2000b). In comparison, the best 2 or 3 Landsat-5 TM broadband OMBVI indices explained 60-89 percent of crop variability (Table 4). Overall, narrowband OMBVI explained 1 to 27 percent greater variability than broadband OMBVI indices. A few illustrations highlight these results. In estimating cumin LAI, the best 3-variable narrowband OMBVI indices explained 22 percent greater variability when compared with best broadband NDVI (Figure 9c and 9d). With only 48 percent canopy cover, cumin is subjected to significant soil background effects that is well modeled using narrowbands centered at 589 nm, 675 nm, and 904 nm (Figure 9c) whereas broadbands fail to capture this variability (Figure 9d).

The narrowband OMBVI (Table 4) performed better than narrowband TBVI (Table 2) 9 times, poorer 8 times, and was equal once (Table 4). The results demonstrate that some combination of 2 or 3 bands provides the best estimates of crop biophysical variables. The sensitivity of any particular portion of a waveband is a function of crop conditions, growth stages, and numerous other factors such as irrigation and soil types. Hence different combinations of bands provide best result (Table 2 and Table 4). For example, the soil background effects were significant in cumin (48 percent canopy cover), and chickpea (69 percent) compared to wheat (97 percent) or barley (97 percent). It is thereby interesting to note that an addition of a third band in OMBVI indices improve R^2 values by 4 to 12 percent in WBM and LAI of cumin and chickpea compared the their best two-band TBVI's (Table 5). By contrast when soil background is insignificant as in case of wheat and barley, addition of third band is not of importance with 3 of the 4 models (WBM of barley, WBM and LAI of wheat; Table 5) showing better R^2 values for 2-band TBVI over 3-band OMBVI.

Comparison of TBVI and OMBVI with various other vegetation indices

Relationships of six other unique narrow and broadband vegetation indices were established with wet biomass (WBM) and leaf area index (LAI) of 6 crops and compared with the narrow and broadband TBVI and OMBVI (Table 5). In 11 of the 12 crop models, the best indices were narrowband versions of either OMBVI or TBVI (see Table 5).

The two-band vegetation index (TBVI) uses best 2 narrow or broadband combinations compared to NDVI, which rigidly uses a NIR and a red band. As a result, there is a significant improvement in estimates of several crop variables using TBVI when compared with NDVI. For example, cumin WBM and LAI (Table 5). NDVI is based on contrast of high reflectance in the NIR and high absorption in the red. NDVI normalizes the topographic effects, is sensitive to photosynthetically active radiation, is a simple and reliable measure of greenness in remotely sensed data for a single date, and is conveniently scaled between -1 and +1. However, NDVI often overestimates vegetation in darker soils compared to brighter soils (Elvidge and Lyon, 1985).

Transformed soil adjusted index (TSAVI) was used since it is expected to account for local changes in soil color, texture, and brightness (Qi et al., 1994, Huete, 1988). TSAVI is amongst the most sensitive vegetation indices (Lawrence and Ripple, 1998). However in this study, TSAVI rarely improved results relative to NDVI (Table 5). In several cases (e.g., barley LAI) narrowband TSAVI significantly decreased R^2 values instead of increasing. It is difficult to attribute the poor performance of TSAVI to any single reason. Determining the precise soil line is crucial to the success of soil adjusted vegetation indices. Soil line is a function of so many variables (e.g., texture, color, organic content) and hence practically difficult to obtain a perfect soil line. Further, even for same soil types, the micro conditions vary even within a field (e.g., moisture-rainfall, irrigation, tillage, drainage, slopes) resulting in the absence of a perfect soil line. Naturally with these problems, a complete accounting of soil background reflectance was not done. Also, normalization of the soil background influences to a constant ratio or a perfect one-dimensional soil line only removes bare soil spectral influences and not the greater soil brightness influences (Huete et al., 1985). With these problems, there is no basis to use soil adjusted vegetation indices with confidence.

The broadband atmospherically corrected indices (ACVI) are computed only for atmospherically effected Landsat-5 TM data and hence the discussion is limited to broadband indices only. Generally, ACVI's, perform slightly better than the broadband NDVI or TSAVI. However, most broadband TBVI and OMBVI indices performed marginally better than ACVI. The results indicate only a marginal improvement with atmospheric correction in majority of models. The ACVI was corrected only for atmospheric scattering and not for atmospheric absorption for which time and location specific climatic data is needed, which is often difficult to obtain.

A significant proportion of the best 3-variable Landsat-5 broadband indices consist of mid infrared bands (TM5 and TM7) indicating the importance of these bands in establishing crop characteristics (Table 4). Mid-infrared bands provide valuable complementary information about the geometric structure of canopies, on optical properties of underlying soils (Boyd and Ripple, 1997 and Boyd et al., 1999) and in handling complex dissimilar growth stages and growing conditions (Thenkabail et al., 1995).

The tassel cap based greenness vegetation index, TCGVI, uses data from 6 non-thermal TM bands and yet explains less variability than 2 band TBVI or multiband OMBVI or red and NIR based NDVI (Table 5). Similarly, broadband and narrowband PCVI (Table 5) computed using principal component derived wavebands 1 and 2 generally perform poorer than NDVI, TBVI, or OMBVI. The coefficients of TCGVI were computed from the TM image of entire study area. Apart from the 6 agricultural crops and rangelands used in this study, the study area consists of many other crops in varying growth stages, agroforests, and several other vegetation and land cover types. These factors result in a more generalized coefficients in TCGVI or PCVI that are less effective for specific crops. In contrast, indices such as TBVI or NDVI use specific wavebands for computing indices for each pixel or farm or crop of interest. However, TCGVI or PCVI might provide more robust equations across crops and for composite mix of vegetations.

Optimal number of narrowbands:band centers and band widths

The frequency of occurrence of narrowbands in the best three TBVI models (Table 2 and 3) and OMBVI models (Table 4) are determined and their distribution in the visible and near infrared spectrum plotted (Figure 10). A overwhelming proportion of crop information is concentrated in few narrowbands. The four most prominent narrowbands are (Figure 10): red absorption maxima between 660 nm to 690 nm, near infrared reflection peak between 900 nm to 920 nm, a portion of red-edge between 700 nm and 720 nm, and green reflectance maxima centered between 540 nm to 560 nm. A more careful evaluation identified information clusters for 12 distinct narrowbands (Table 6). The 12 optimal narrowbands in the visible and NIR are: 1 blue, 3 green, 3 red, 1 red-edge, 1 NIR, 2 NIR peak, and 1 NIR moisture sensitive. The bandwidths are defined as: very narrow (less than or equal to 15 nanometers) or narrow (15 to 30 nm) or broad (greater than 30 nm). Based on this definition, only the band 9 with 120 nm is broadband (Table 6). The other 11 bands are narrowband (Table 6). The band centers and bandwidths presented in Table 6 are derived from the results of Tables 2, 3, and 4 and Figures such as 4, 5, and 10. The band centers and widths are rounded off to nearest 5's or 10's (e.g., 718 nm as 720 nm). A number of these band centers are positioned where the soil (fallow farms) and vegetation have slopes intersect and head in opposite directions (see Figure 3) resulting in increased sensitivity of indices using this portion of the spectrum. For example, at 570 nm for chickpea and cumin and 720 nm for wheat.

The best 2 band indices, TBVI's, can be formulated using narrowband combinations of a red and a NIR peak, or a red and a NIR "shoulder", or a red-edge and a NIR peak, or a red-edge and a NIR shoulder, or a green and a red band combinations (Table 2 and 3). Bandwidths can vary between 5 nm to 30 nm (Table 6). Waveband along the NIR "shoulder" can either be a broadband or a narrowband providing similar results. For 3-variable multi linear OMBVI models, band combinations that provide the best results are, typically, combinations of any 3 narrowbands consisting of red, NIR peak, red-edge, blue, or green. In Landsat-5 TM a red (TM3) and a NIR

(TM4) band provides the best results followed by the green (TM2) band (Figure 11 and Table 2 and 4). Narrowband versions of these bands are (Table 6): band 6 (λ = 675 nm, $\Delta\lambda$=15 nm), band 10 or 11 (λ = 905 or 920 nm, $\Delta\lambda$=15 nm), and band 3 (λ = 550 nm, $\Delta\lambda$=25 nm). For example, barley dry biomass was estimated with an R^2 value of 0.81 using narrowbands centered at 670 nm and 910 nm compared to a best R^2 value of 0.76 using broadbands TM3 and TM4 (Table 2). Common vegetation reflectance peaks around 900nm to 940 nm and absorption peaks around 670 nm or 690 nm (e.g., Figure 3) provide maximal crop information. These results confirm Blackburn (1998 and 1999) who found Chlorophyll a and b of crops or vegetation to be most strongly correlated around 670 nm and 680 nm.

The structure of plant canopies has a significant bearing on spectral signature. For example, the planophile (30 degrees) structure of canopies of legumes such as vetch and lentil contribute significantly to greater reflectance in NIR and greater absorption in red compared to erectophile (65 degrees) structure of wheat and barley (Figure 3a and 3b). The erectophile structure leads to significant slope changes in spectra in the region of 740 nm to 940 nm. Thenkabail et al. (2000b) had highlighted the importance of a narrow NIR band centered around 920 nm along with narrow red band centered at 682 nm for establishing crop characteristics. In comparison to narrowbands, TM3 (630-690 nm) and TM4 (760-900 nm) broadbands capture a wide range of average conditions but miss out on specific or optimal conditions centered on specific narrow wavelengths. These results agree with recent results by Blackburn and Steele (1999), that the broadband derived simple ratio vegetation index or NDVI were unrelated to either pigment concentrations, LAI or percent cover whereas LAI and percent cover were strongly related to narrow waveband derived ratios.

The above results further indicate that the optimal information on crops are not necessarily concentrated in the red and NIR wavelengths but are often in other portions of the wavebands such as red-edge or green or moisture sensitive NIR. For example, chickpea WBM is best-modeled using 2 visible bands: a green band centered at 568 nm ($\Delta\lambda_1 = 10$) and a red band centered at 678 nm ($\Delta\lambda_2 = 10$) (Figure 5, Table 2). The visible spectrum is very sensitive to loss of chlorophyll, browning, ripening, and senescing (Idso et al., 1980), carotenoid (Blackburn, 1998; Tucker, 1977), soil background effects, and crop senescing rates and grain yield prediction (Idso et al., 1980). Changes in pigment content and chloroplast for different crop type, growth stage, and growing conditions can cause sensitivity around 568 nm and 520 nm (Nichol et al., 2000) resulting in dramatic shifts in crop-soil spectral behavior (Figure 3a through 3d). Similarly, vetch LAI is best modeled using a red-edge centered at 720 nm ($\Delta\lambda_1 = 6$) and a NIR peak centered at 910 nm ($\Delta\lambda_2 = 10$) (Table 2). Several wavebands found along the red-edge (701 nm through 740 nm) appear prominently in the best crop models (Table 2) especially for mixed growing conditions, conditions of stress, and background effects (Clevers, 1999; Dawson and Curran, 1998; Elvidge and Chen, 1995; and Shaw et al., 1998). Amongst the other optimal bands (Table 6), band 3 ($\lambda = 550$ nm) is strongly correlated with total chlorophyll (Schepers et al., 1996), and band 1 ($\lambda = 490$ nm) with carotenoid, leaf chlorophyll, and senescing conditions (Aoki et al., 1981; Gitelson et al., 1996; and Tucker, 1977). As biomass and moisture in crops increase, absorption in the moisture sensitive portion of NIR shoulder (940 nm to 1010 nm) also increases (see Figure 3a through 3d). The mean wet biomass (kg/m^2) in decreasing order of magnitude was: wheat (3.28), vetch (3.22), barley (2.54), lentil (2.49), chickpea (1.41), marginal lands (0.90), and cumin (0.82). The mean spectral plots (Figure 3a through 3d) clearly indicate significantly larger "trough" in 940 nm to 1010 nm for vetch, lentil, wheat, and barley compared to chickpea, cumin, and marginal lands. Two of the best OMBVI models, those for cumin WBM and barley LAI, involve biomass or moisture sensitive NIR bands centered at 989 nm (Table 4).

Similarly, chickpea dry biomass is best estimated using a 965 nm centered narrowband. Overall, taking the results of all TBVI and OMBVI models a moisture sensitive NIR band centered at 975 nm ($\Delta\lambda$= 15 nm) is considered optimal (Table 6). Solar irradiant energy and sensitivity of light detectors are relatively higher at 960 nm than in the water absorption bands at 1450 nm and 1900 nm (Penuelas et al., 1993). The derivative of the canopy reflectance spectrum at 960 nm detected difference between water stressed and non-stressed canopies of rice before symptoms were visible and before NDVI could detect such a stress (Peñuelas et al., 1995; Shibayama et al., 1993).

The twelve optimal bands (Table 6) compare reasonably well with an earlier study by Thenkabail et al. (2000b) which also recommended 12 bands based on a study of 5 different crops in the summer growing season. For example, the 3 green bands in this study were centered at 520 nm, 550 nm, and 575 nm compared to the 3 green bands of Thenkabail et al. (2000b) which were centered at 525 nm, 550 nm, and 568 nm. In the red portion the three bands in this study were centered at 660 nm, 675 nm, and 700 nm compared to 668 nm, 682 nm, and 696 nm of Thenkabail et al. (2000b). Overall, there were only minor differences in band centers and bandwidths.

Conclusions

The study established that the optimal agricultural crop and rangeland biophysical information could be obtained using only 12 of the 430 hyperspectral bands in the visible and near infrared portion of the spectrum. The research was based on hyperspectral narrowband and Landsat-5 TM broadband data for six agricultural crops (barley, wheat, chickpea, lentil, vetch, and cumin) and marginal lands. Biophysical variables included leaf area index, wet and dry biomass, canopy cover, plant height, and plant nitrogen. Narrowband data was gathered using 430 discrete narrowbands, each of 1.43 nm wide and in the spectral range of 395 nm to 1010 nm. Broadband data was acquired to coincide with field spectral and biophysical measurements. Data from 6 non-thermal bands (450 nm to 2350 nm) of Landsat-5 TM were used.

The main focus in this paper was to conduct a rigorous evaluation of narrowband: (a) Two band vegetation indices (TBVI), and (b) Optimum multiple band vegetation indices (OMBVI), and compare them with six other categories of narrow and broadband indices. The six other narrowband and broadband indices are: red and NIR based normalized difference NDVI, transformed soil adjusted TSAVI, atmospheric corrected ACVI, middle infrared based MIVI, tassel cap greenness TCGVI, and principal component based PCVI. The narrowband TBVI were used to perform a rigorous search procedure involving 430 bands to identify the best NDVI predictors of crop biophysical variables and are illustrated using special lambda (λ_1) versus lambda (λ_2) plots of R^2 values. The piecewise linear regression models involving 430 bands are run to determine the best 1-variable, 2-variable, to n-variable narrowband OMBVI models for each crop variable.

Twelve bands provided optimal biophysical information (Table 6). The bandwidths for 11 of the 12 optimal bands are narrow (less than 30 nm). Only one band, NIR “shoulder”, centered at 845 nm has broad (greater than 30 nm) bandwidth. A overwhelming proportion of crop information was concentrated in a few narrowbands (Figure 10). The most prominent narrowbands, in order of importance, occur in following waveband ranges: 660 to 690 nm (red-absorption maxima), 900 to 925 nm (near infrared reflection peak), 700 and 720 nm (a portion of red-edge), and 540 to 555 nm (green reflectance maxima). These are followed by other bands that provide significant crop growth and yield information: a blue band of rapid change in slope of the spectra per unit change in wavelength centered around 490 nm, 2 green bands centered at 520 nm and 575 nm providing most rapid positive or negative change in reflectance per unit change in wavelength anywhere in the visible portion of the spectrum, center of NIR "shoulder" centered at 845 nm, and a biomass/moisture sensitive band centered around 975 nm. The identification of optimal bands serve 2 main purposes: (1) help select wavebands most needed for an application from hyperspectral datasets, and/or (2) help select wavebands for application specific sensors onboard next generation of satellites. This study established that 418 of the 430 bands were redundant in providing agricultural crop biophysical information. Thus, the optimal bands suggested in this paper are likely to help reduce: data redundancy, data volumes, and time and resources involved in image interpretation and analysis.

References

Aoki, M., Yabuki, K. and Totsuka, T., 1981. An evaluation of chlorophyll content of leaves based on the spectral reflectivity in several plants, Res. Rep. Natl. Inst. Environ. Stud. Jpn. 66, pp. 125-130.

Asner, G.P., Wessman, C.A., Bateson, C.A., Privette, J.L. 2000. Impact of Tissue, Canopy, and Landscape Factors on the Hyperspectral Reflectance Variability of Arid Ecosystems, Remote Sensing of Environment, 74(1), pp. 69-84.

Badhwar, G.D., and Henderson, K.E. 1981. Estimating developmental stages of corn using spectral data-an initial model, *Agronomy Journal*, 73:748-755.

Baret, F., Guyot, G., Major, D.J. 1989. TSAVI: A vegetation index which minimizes soil brightness effects on LAI and APAR estimation, *in Proceedings of the 12th Canadian Symposium on Remote Sensing*, IGARRS'90, Vancouver, BC, Canada, 10-14 July. 3:1355-1358.

Blackburn, G.A., 1998. Spectral indices for estimating photosynthetic pigment concentrations: a test using senescent tree leaves, INTERNATIONAL JOURNAL OF REMOTE SENSING, 19 (4): 657-675

Blackburn, G.A. 1999. Relationships between Spectral Reflectance and Pigment Concentrations in Stacks of Deciduous Broadleaves, Remote Sensing of Environment, 70(2), pp. 224-237.

Blackburn, G.A., Steele, C.M. 1999. Relationships between Spectral Reflectance, Pigment, and Biophysical Characteristics of Semiarid Bushland Canopies, Remote Sensing of Environment, 70(3), pp. 278-292.

Boyd, D.S., and Ripple, W.J., 1997. Potential vegetation indices for determining global forest cover, International Journal of Remote sensing, 18(6): 1395-1401.

Boyd, D.S., Foody, G.M., and Curran, P.J. 1999. The relationship between the biomass of Cameroonian tropical forests and radiation reflected in middle infrared wavelengths (3.0-5.0 μm), International Journal of Remote Sensing, 20(5):1017-1023.

Carter, G.A., 1994. Ratios of leaf reflectance's in narrow wavebands as indicators of plant stress, Int. J. Remote Sens, 15, pp. 697¯703.

Carter, G.A., 1997. Reflectance wavebands and indices for remote estimation of photosynthesis and stomatal conductance in pine canopies, *Remote Sensing of Environment,* 63:61-72.

Carter, G.A., 1998. Reflectance bands and indices for remote estimation of photosynthesis and stomatal conductance in pine canopies, *Remote Sensing of Environment,* 63:61-72.

Chavez, P.S., 1988. An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data, *Remote Sensing of Environment*, 24, 459-479.

Chavez, P.S., 1989. Radiometric calibration of Landsat thematic mapper multispectral images, *Photogrammetric Engineering and Remote Sensing*, 55, 1285-1294.

Clark, R.N., G.A. Swayze, T.V.V. King, K.E. Livo, R.F. Kokaly, J.B. Dalton, J.S. Vance, B.W. Rockwell, R. R. McDougal, 1998. Surface Reflectance Calibration of Terrestrial Imaging Spectroscopy Data: a Tutorial Using AVIRIS, U.S. Geological Survey, Open File Report.

Clevers, J.G.P.W. 1999. The use of imaging spectrometry for agricultural applications, ISPRS Journal of Photogrammetry and Remote Sensing, 54(5-6):299-304.

Curran, P.J., J.L. Dungan, and Gholz, H.L. 1990. Exploring the relationship between reflectance red edge and chlorophyll content in slash pine, *Tree Physiology,* 7:33-48.

Curran, P.J., Dungan, J.L., Macler, B.A. and Plummer, S.E., 1991. The effect of a red leaf pigment on the relationship between red-edge and chlorophyll concentration, Remote Sens. Environ., 35, pp. 69-75.

Dawson, T.P., Curran, P.J. 1998. A new technique for interpolating the reflectance red edge position. International Journal of Remote Sensing , 19 (11): 2133-2139.

Elmore, A.J., Mustard, J.F., Manning, S.J., Lobell, D.B., 2000. Quantifying Vegetation Change in Semiarid Environments: Precision and Accuracy of Spectral Mixture Analysis and the Normalized Difference Vegetation Index, Remote Sensing of Environment, 73(1), pp. 87-102.

Elvidge, C.D. and Chen, Z., 1995. Comparison of broadband and narrow-band red and near-infrared vegetation indices, Remote Sensing of Environment, 54, pp. 38-48.

Elvidge, C.D. and Lyon, R.J.P., 1985. Influence of rock-soil variation on the assessment of green biomass, Remote Sensing of Environment, 17, pp. 265¯279.

Fassnacht, K.S., Gower, S.T., MacKenzie, M.D., Nordheim, E.V., and Lillesand, T.M. 1997. Estimating the leaf area index of north central Wisconsin forests using the landsat thematic mapper, Remote Sensing of Environment. 61:229-245.

FieldSPEC. 1997. User's Guide, manual release, Analytical Spectral Devices, Inc. Boulder, Colorado, USA.

Friedl, M.A., Michaelsen, J., Davis, F.W., Walker, H., and Schimel, D.S. 1994. Estimating Grassland Biomass and Leaf Area Index Using Ground and Satellite Data, *International Journal of Remote Sensing*, 15(7):1401-1420.

Gat Nahum (editor), 1995. Hyperspectrum newsletter. 2(1).

Gitelson, A.A., Merzlyak, M.N., 1996. Signature analysis of leaf reflectance spectra: Algorithm development for remote sensing of chlorophyll, JOURNAL OF PLANT PHYSIOLOGY, 148: (3-4):494-500.

Goetz, A.F.H, G. Vane, J.E. Solomon, and B.N. Rock, 1985, Imaging spectrometry for earth remote sensing, Science, 228, 1147-1153.

Gong, P., Pu, R., Miller, J.R. 1995. Coniferous forest leaf area index estimation along the Oregon transect using compact airborne spectrographic imager data, Photogrammetric Engineering and Remote Sensing. 61(9):1107-1117.

Huete, A.R., Jackson, R.D., and Post, D.F. 1985. Spectral response of a plant canopy with different soil backgrounds, *Remote Sensing of Environments,* 17:37-53.

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI), Remote Sensing of Environment. 25, pp. 295-309.

Idso. B., P.J. Pinter, Jr., R.D. Jackson, and Reginato R.J. 1980. Estimation of grain yields by remote sensing of crop senescence rates, *Remote Sensing of Environments,* 9:87-91.

Jacobsen, A., Heidebrecht, K.B., and Goetz, A.F.H. 2000. Assessing the quality of the radiometric and spectral calibration of casi data and retrieval of surface reflectance factors, Photogrammetric Engineering and Remote Sensing, 66(9): 1083-1091.

Jackson, R.D., 1983. Spectral Indices in n-Space. *Remote Sensing of Environment*, 13:409-421.

Jensen, J. R., 1996. Introductory Digital Image Processing: A Remote Sensing Perspective, Prentice-Hall, Inc., 231 p.

Kaufman, Y.J., Tanre,D. 1996. Strategy for direct and indirect methods for correcting the aerosol effect on remote sensing from AVHRR to EOS-MODIS, Remote Sensing of Environment, 55:65-79.

Lawrence, R.L., Ripple W.J. 1998, Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape:Mount St. Helens, Washington, *Remote sensing of Environment*, 64:91-102.

Lichtenthaler, H.K., Gitelson, A.A. and Lang, M., 1996. Non-destructive determination of chlorophyll content of leaves of a green and an aurea mutant of tobacco by reflectance measurements, J. Plant Physiol., 148, pp. 483-493.

Lyon, J.G., Yuan, D., Lunetta, R.S. and Elvidge, C.D., 1998. A change detection experiment using vegetation indices, Photogramm. Eng. Remote Sens., 64, pp. 143-150.

Markham, B.L, and Barker, J.L., 1985. Spectral characterization of the LANDSAT Thematic Mapper sensors, International Journal of Remote sensing, 6(5):697-716.

Markham, B.L, and Barker, J.L., 1987. Radiometric properties of U.S. processed Landsat MSS data. Remote Sensing of Environment, 22:39-71.

Mass, S.J. 2000. Linear Mixture Modeling Approach for Estimating Cotton Canopy Ground Cover using Satellite Multispectral Imagery, Remote Sensing of Environment, 72(3), pp. 304-308.

Mariotti, M., Ercoli, L. and Masoni, A., 1996. Spectral properties of iron-deficient corn and sunflower leaves, Remote Sens. Environ., 58, pp. 282-288.

McGwire, K., Minor, T., Fenstermaker, L. 2000. Hyperspectral Mixture Modeling for Quantifying Sparse Vegetation Cover in Arid Environments, 72(3):360-374.

Milton, E.J., 1994. Teaching atmospheric correction using a spreadsheet. Photogrammetric Engineering and Remote Sensing, 60, 751-754.

Nickel, H., and Labs, D., 1981. Improved data of solar spectral irradiance from 0.33 to 1.25 μm. Solar Physics, 74:231-240.

Nickel, H., and Labs, D., 1984. The solar radiation between 3300 and 12500 A, Solar Physics, 90:205-258.

Nichol, C.J., Huemmrich1, K.F., Black, T.A., Jarvis, P.G., Walthall, C.L., Grace, J., Hall, F.G., 2000. Remote sensing of photosynthetic-light-use efficiency of boreal forest, Agricultural and Forest meteorology, 101(2-3): 131-142.

Nolin, A.W., and Dozier, J., 2000. A Hyperspectral Method for Remotely Sensing the Grain Size of Snow, Remote Sensing of Environment, 74(2), pp. 207-216.

Penuelas, J., Filella, I., Biel, C., Serrano, L., Save, R. 1993. The reflectance at the 950-970 region as an indicator of plant water status, *International Journal of Remote Sensing*, 14(10):1887-1905.

Penuelas, J., I. Filella, P. Lloret, F. Munoz and M. Vilajeliu. 1995. Reflectance assessment of mite effects on apple trees, Int. J. Remote Sens., 16:2727-2733.

Price, J.C., 1987. Special Issue on Radiometric Calibration of Satellite Data, Remote Sensing of Environment, 22(1): 1-158.

Qi, J., Chehbouni, A., Huete, A., Kerr, Y. and Sorooshian, S., 1994. A modified soil-adjusted vegetation index (MSAVI), Remote Sensing of Environment, 48, pp. 119¯126.

Richardson, A.J., Wiegand, C.L., Wanjura, D.F., Dusek, D., Sreiner, J.L. 1992. Multisite analysis of spectral-biophysical data for sorphum, *Remote Sensing of Environment,* 47:71-82.

Richery, J.E., Adams, J.B., and Victoria, R.L., 1989. Synoptic-Scale Hydrological and Biogeochemical Cycles in the Amazon River Basin: A Modelling and Remote Sensing Perspective, In Remote Sensing of Biosphere Functioning, (Editors: Hobbs R.J., and Mooney, H.A.), *Ecological Studies 79*, Springer-Verlag, New York. Pp.249-268.

SAS Institute, 1997. SAS/STAT User's Guide and Software Release 6.12 Edition (Cary, North Carolina: SAS Institute Inc.).

Rouse, J.W., Jr., Haas, R.H., Schell, J.A., and Deering, D.W., 1973. Monitoring Vegetation Systems in the Great Plains with ERTS, in Third ERTS Symposium, *NASA SP-351, U.S. Govt. Printing Office*, Washington DC, Vol. 1, pp.309-317.

Ryan, J., Masri, S., Garabet, J., Diekmann, J., and Habib, H. 1997. Soils of ICARDA's agricultural experimental stations and sites: climate, classification, physical and chemical properties, and land use, *International Center for Agricultural Research in the Dry Areas (ICARDA*), Aleppo, Syria. Vi+ 107 pp.

Sanderson, E.W., Zhang, M., Ustin, S.L. and E. Rejmankova. 1998. A method of scaling up to AVIRIS pixel size using geostatistics, Landscape Ecology, 13: 79-92.

Schepers, J.S., Blackmer, T.M., Wilhelm, W.W., and Resende, M., 1996. Transmittance and reflectance measurements of corn leaves from plants with different nitrogen and water supply, J. Plant Phys., 148:523-529.

Shaw, D.T., Malthus T.J., Kupiec, J.A. 1998. High-spectral resolution data for monitoring Scots pine (Pinus sylvestris L.) regeneration, International Journal of Remote Sensing, 19 (13): 2601 -- 2608.

Shibayama. M., Akiyama T. 1991. Estimating grain yield of maturing rice canopies using high spectral resolution reflectance measurements, *Remote Sensing of Environment*, 36:45-53.

Shibayama, M., Takahashi, W., Morinaga, S., and Akiyama, T. 1993. Canopy water deficit detection in paddy rice using high resolution field Spectroradiometer, *Remote Sensing of Environment*, 45:117-126.

Thenkabail P.S. 1999. Characterisation of the Alternative to slash-and-burn benchmark research area representing the Congolese rainforests of Africa using near-real-time SPOT HRV data, The International Journal of Remote Sensing, 20(5):839-877.

Thenkabail P.S. 2001. Design of an optimal hyperspectral sensor for estimating agricultural crop characterisitcs using discriminant model and principal component analysis. Manuscript in preparation.

Thenkabail P.S., Smith, R.B., and De Pauw, E. 1999. Hyperspectral vegetation indices for determining agricultural crop characteristics. CEO research publication series # 1. ISBN: 0-9671303-0-1, Center for Earth Observation, Yale University, USA.

Thenkabail, P.S., Nolte. C., Lyon, J.G. 2000a. Remote sensing and GIS modeling for selection of a benchmark research area in the inland valley agroecosystems of West and Central Africa. Photogrammetric Engineering and Remote Sensing, Special issue: GIS applications in Africa, 66(6): 755-768.

Thenkabail, P.S., Smith, R.B., and De Pauw, E. 2000b. Hyperspectral Vegetation Indices for determining agricultural crop characteristics, Remote Sensing of Environment, 71:158-182.

Thenkabail, P.S., Ward, A.D., and Lyon, J.G., 1995. Landsat-5 Thematic Mapper models of soybean and corn crop characteristics, *International Journal of Remote Sensing*, **15**, 49-61.

Tucker, C.J. 1977. Spectral estimation of grass canopy variables, *Remote Sensing of Environment*, 6:11-26.

Tucker, C.J. 1980. Remote Sensing of Leaf Water Content in the Near Infrared, Remote Sensing of Environment, 10:23-32.

Vaesen, K., Gilliams, S., Nackaerts, K., and Coppin, P. 2001. Ground-measured spectral signatures as indicators of ground cover and leaf area index: the case of paddy rice. Field Crops Research, 69 (1):13-25.

Wiegand, C.L., Mass, S.J., Aase, J.K., Hatfield, J.L., Pinter, P.J., Jr., Jackson, R.D., Kanemasu, E.T., Lapitan, R.L. 1992. Multisite analysis of spectral-biophysical data for wheat, *Remote Sensing of Environment*, 42:1-21.

Acknowledgements

The authors would like to thank Prof. Dr. Adel El-Beltagy, Director General and Dr. John H. Dodds, Assistant Director General (Research) of the International Center for Agricultural Research in the Dry Areas (ICARDA) for permission and support to conduct this research using ICARDA facilities. Mr. Afif Dakermanji, Mr. Pierre Hayak, Mr. A.F. Tarsha, Dr. Diekman, Mr. Zuhair Masry, Mr. Samir Masri and Dr. John Ryan of ICARDA provided invaluable and cheerful support in gathering and analysing ground truth data. Thanks are due to our colleagues Dr. Laurent Bonneau, Dr. Steven Skubis, and Dr. Roland Geerken at the Center for Earth Observation (CEO), Yale University for the useful interactions or discussions or support at various stages of this research. The funding for the project comes from the National Aeronautics and Space Administration (NASA) Earth Science Enterprise (formerly, Mission to Planet Earth) grant number NAG5-3853.

List of Tables

List of Figures

Figure 1. Part of the study area showing land cover classes mapped using Landsat-5 TM draped over 10 m DEM from the Russian KVR-1000. Color key: dark green=cereals (wheat, barley), light green=legumes (lentil,vetch,cowpea), cyan=cumin, yellow=marginal lands type 1, dark gray=marginal lands type 2, magenta=agroforests, brown=fallow farms, white or light gray=built-up, blue=roads or farm roads.

Figure 2. Illustrations of representative farms depicting typical growth stages, canopy cover, field sizes, and other visual characteristics like pigmentation of 6 spring crops used in this study.

Figure 3. Average spectral characteristics of 6 crops, marginal lands, and fallow farms.

Figure 4. Contour plot of R^2 values depicting relationships between LAI and two band vegetation indices (TBVI's) for crops (a) wheat (above the diagonal), and (b) barley (below the diagonal).

Figure 5. Contour plot of R^2 values depicting relationships between wet biomass and two band vegetation indices (TBVI's) for crops (a) chickpea (above the diagonal), and (b) lentil (below the diagonal).

Figure 6. Generic relationships involving broadband Landsat-5 TM NDVI's of all 6 crops with (a) LAI and (b) wet biomass.

Figure 7. Generic relationships involving a NIR and red based narrowband two-band vegetation index (TBVI) of all 6 crops with (a) LAI and (b) wet biomass.

Figure 8. Plot comparing the narrowband and broadband relationships with wheat and barley wet biomass.

Figure 9. Plot comparing the narrowband and broadband relationships with wheat and cumin LAI.

Figure 10. Distribution of narrowband information clusters. The most frequently occurring narrowbands in models that provide the best estimates of biophysical characteristics.

Figure 11. Distribution of broadband Landsat-5 TM information clusters. The most frequently occurring broadbands in models that provide the best estimates of biophysical characteristics.

Table 1. Narrowband and broadband data used in this study compared with spaceborne Hyperion and Airborne AVIRIS sensors.

Sensor	wavelength (nanometers)	spectral Resolution (nanometers)	number of Bands (#)	spatial resolution (meters)	area per pixel (m^2)	pixels per hectare (#)
1. Narrow band data For this study from Spectroradiometer (visible and NIR)	395-1010*	1.43	430	0.38**	0.1133**	88219
2. Broad band data For this study from Landst-5 TM	450-2350	band 1: 70 nm band 2: 80 nm band 3: 60 nm band 4:140 nm band 5: 20 nm band 7: 27 nm	6	30	900	11.11
3. Hyperion	400-2500	10	220	30	900	11.11
4. AVIRIS	400-2500	10	224	20	400	25

Note:

* = visible and near infrared (VNIR) spectroradiometer is in 350-1050 nm range. However, only 395-1010 nm range of spectrum was considered to avoid the significant noise in the early and late waveband portions.

** = area when spectroradiometer was held at 1.2 meter above ground level with 18 degree field of view (FOV) resulting in the diameter of 0.38 m and area (πr^2) of 0.113354 m^2 (or 1133 cm^2).

Table 2. Models providing best R^2 values for estimating various biophysical variables using NDVI-type narrowband and Landsat-5 broadband two-band vegetation indices (TBVI's).

Crop	**Variable**	**Landsat-5 TM data**				**Hyperspectral data**						**Increased variability explained by the best hyperspectral index when compared with the best Landsat-5 TM index (percent)**
		Best index		**Second best index**		**Best index**		**Second best index**		**Third best index**		
		Spectral band centers in NDVI-type index	**R^2**	**Spectral band centers in NDVI-type index R^2**	**R^2**	**spectral band centers in NDVI-type index**	**R^2**	**spectral band centers in NDVI-type index**	**R^2**	**spectral band centers in NDVI-type index**	**R^2**	
1. Barley^A (44)	WBM	TM3,TM4	0.75	TM2,TM3	0.69	675,820	0.84	495,525	0.80	455,840	0.78	9
	DBM	TM3,TM4	0.76	TM2,TM4	0.65	670,910	0.81	675,760	0.80	550,568	0.75	5
	LAI	TM3,TM4	0.71	TM2,TM3	0.62	720,815	0.79	675,700	0.76	550,590	0.73	8
	PLNTHT	TM2,TM3	0.44	TM3,TM4	0.40	670,905	0.45	675,575	0.43	410,920	0.40	1
2. Wheat^A (64)	WBM	TM2,TM4	0.70	TM2,TM4	0.67	604,904	0.83	590,845	0.81	550,590	0.61	13
	DBM	TM3,TM4	0.65	TM2,TM4	0.64	545,910	0.80	700,910	0.79	550,830	0.74	15
	LAI	TM2,TM4	0.66	TM2,TM4	0.66	680,910	0.74	515,910	0.73	635,880	0.72	8
	PLNTHT	TM3,TM4	0.37	TM2,TM4	0.36	437,880	0.41	550,880	0.39	715,860	0.34	4
3. Lentil^A (23)	WBM	TM3,TM4	0.80	TM2,TM3	0.74	675,910	0.85	418,904	0.82	550,675	0.81	5
	DBM	TM3,TM4	0.68	TM2,TM4	0.64	675,845	0.78	675,985	0.75	550,678	0.73	10
	LAI	TM3,TM4	0.78	TM1,TM3	0.71	670,845	0.84	445,905	0.84	675,975	0.81	6
	PLNTHT	TM1,TM3	0.26	TM3,TM4	0.24	675,910	0.50	680,980	0.49	646,680	0.48	24
4. Cumin ^{B} (17)	WBM	TM2,TM4	0.75	TM2,TM3	0.69	678,880	0.80	568,675	0.79	678,920	0.75	5
	DBM	TM2,TM4	0.71	TM2,TM4	0.67	675,800	0.87	568,678	0.81	495,880	0.78	20
	LAI	TM3,TM4	0.70	TM1,TM3	0.64	568,661	0.85	678,775	0.83	490,845	0.83	15
	PLNTHT	TM3,TM7	0.15	TM3,TM4	0.06		NS		NS		NS	NA
5. Chickpea^A (14)	WBM	TM3,TM4	0.86	TM2,TM4	0.79	568,678	0.95	670,810	0.95	495,820	0.94	9
	DBM	TM3,TM4	0.72	TM2,TM3	0.68	750,965	0.91	760,775	0.91	535,620	0.89	21

	LAI	TM3,TM4	0.78	TM2,TM3	0.71	720,840	0.92	495,840	0.91	550,680	0.89	14
	PLNTHT	TM3,TM4	0.83	TM5,TM7	0.79	690,840	0.96	550,680	0.95	495,845	0.93	8
6. Vetch ^{B} (14)	WBM	TM3,TM5	0.74	TM3,TM4	0.73	675,820	0.82	418,661	0.70	520,604	0.63	8
	DBM	TM3,TM5	0.72	TM2,TM4	0.65	715,910	0.84	550,880	0.72	525,575	0.67	11
	LAI	TM3,TM5	0.77	TM3,TM4	0.65	720,910	0.80	568,910	0.68	460,920	0.64	3
	PLNTHT	TM1,TM5	0.11	TM5,TM7	0.11	668,682	0.24	965,982	0.28	765,965	0.13	13
7. Marginal^{A} (20)	WBM	TM2,TM3	0.87	TM3,TM4	0.83	672,906	0.89	568,675	0.80	418,525	0.77	2
	DBM	TM2,TM3	0.78	TM1,TM3	0.82	680,908	0.80	437,910	0.76	550,682	0.69	2

Note: A = Non-linear exponential models of the type $Y=a*e^{b*x}$; B = Linear models of the type Y = a + b * x
NS = not significant, NA = not available.

Table 3. Band centers (λ_1 and λ_2) and bandwidths ($\Delta\lambda_1$ and $\Delta\lambda_2$) for models that provide best estimates of biophysical characteristics using hyperspectral narrowband Two-band vegetation indices (TBVI's)[AA].

Crop (symbol) (sample size)	**Crop Variable (units)**	**Band center and width (nm)**	**Band-centers (λ_1 and λ_2) and band-widths ($\Delta\lambda_1$ and $\Delta\lambda_2$) for two-band vegetation indices**		
			Index 1[BB] (nm)	**Index 2 (nm)**	**Index 3 (nm)**
1. Barley (44)	**WBM (kg/m^2)**	λ_1	675	495	455
		$\Delta\lambda_1$	10	20	45
		λ_2	820	525	820
		$\Delta\lambda_2$	200	20	160
	LAI (m^2/m^2)	λ_1	720	675	550
		$\Delta\lambda_1$	10	6	20
		λ_2	815	700	590
		$\Delta\lambda_2$	130	6	20
2. Wheat (64)	**WBM (kg/m^2)**	λ_1	604	590	550
		$\Delta\lambda_1$	45	20	10
		λ_2	904	845	590
		$\Delta\lambda_2$	6	90	10
	LAI (m^2/m^2)	λ_1	680	495	635
		$\Delta\lambda_1$	20	60	30
		λ_2	910	910	880
		$\Delta\lambda_2$	20	30	10
3. Lentil (23)	**WBM (kg/m^2)**	λ_1	675	418	550
		$\Delta\lambda_1$	15	75	45
		λ_2	910	904	675
		$\Delta\lambda_2$	15	10	15
	LAI (m^2/m^2)	λ_1	670	445	675
		$\Delta\lambda_1$	20	75	6
		λ_2	845	905	975
		$\Delta\lambda_2$	160	20	10
4. Cumin (17)	**WBM (kg/m^2)**	λ_1	678	568	678
		$\Delta\lambda_1$	6	20	6
		λ_2	880	675	920
		$\Delta\lambda_2$	40	6	6
	LAI (m^2/m^2)	λ_1	568	678	490
		$\Delta\lambda_1$	30	20	20
		λ_2	661	775	845
		$\Delta\lambda_2$	20	60	120
5. Chickpea (14)	**WBM (kg/m^2)**	λ_1	568	670	495
		$\Delta\lambda_1$	10	45	20
		λ_2	678	820	820
		$\Delta\lambda_2$	10	160	160
	LAI (m^2/m^2)	λ_1	720	495	550
		$\Delta\lambda_1$	30	30	60
		λ_2	840	840	680
		$\Delta\lambda_2$	120	120	30
6. Vetch (14)	**WBM (kg/m^2)**	λ_1	680	418	520
		$\Delta\lambda_1$	45	20	20
		λ_2	920	661	604
		$\Delta\lambda_2$	30	20	20
	LAI (m^2/m^2)	λ_1	720	568	460
		$\Delta\lambda_1$	6	6	6
		λ_2	910	910	920
		$\Delta\lambda_2$	10	10	10
7. Marginal lands (14)	**WBM (kg/m^2)**	λ_1	672	568	418
		$\Delta\lambda_1$	10	10	6
		λ_2	906	675	530
		$\Delta\lambda_2$	10	10	10

Table 4. Models providing best R^2 values for estimating various biophysical variables using 1, 2, or 3 variable narrowband and broadband optimum multiple band vegetation indices (OMBVI's) ^{AA,BB}.

Crop type (sample size)	**Dependant crop variable**	**Hyperspectral data**						**Landsat TM data**		**Best norm veget (thes 4)**
		Best 1 variable model OMNBR (best 1 variable models)		**Best 2 variable model OMNBR (best 2 variable models)**		**Best 3 variable model OMNBR (best 3 variable models)**		**Best 2 or 3 variable model OMNBR (best 3 variable models)**		
		Band centers (nm)^{CC} (independent variable)	**R^2 value**	**Band centers (nm)^{CC} (independent variables)**	**R^2 value**	**Band centers (nm)^{CC} (independent variables)**	**R^2 value**	**TM bands (independent variables)**	**R^2 value**	**broa band Land TM NDV mode**
1. Barley (44)	**WBM**	675	0.56	675,904	0.77	418,675,904	0.80	TM3,TM4	0.68	0.75
	DBM	675	0.49	646,718	0.77	461,632,704	0.80	TM3,TM4	0.69	0.76
	LAI	675	0.44	704,904	0.77	704,904,989	**0.82**	TM3,TM4	0.64	0.71
2. Wheat (64)	**WBM**	904	0.49	518,904	0.74	518,575,904	0.76	TM2,TM4	0.60	0.70
	DBM	604	0.38	547,904	0.62	547,904,932	0.67	TM4,TM5	0.60	0.65
	LAI	675	0.41	718,904	0.56	704,904,918	0.60	TM3,TM4	0.60	0.66
3. Lentil (23)	**WBM**	675	0.65	675,904	0.76	646,804,918	0.82	TM3,TM4	0.82	0.80
	DBM	675	0.58	404,675	0.66	575,675,961	0.71	TM3,TM4,TM5	0.64	0.68
	LAI	675	0.70	475,547	0.83	461,475,541	**0.84**	TM2,TM4	0.79	0.78
4. Cumin (17)	**WBM**	675	0.42	675,704	0.84	675,704,989	**0.89**	TM2,TM4	0.77	0.75
	DBM	661	0.59	489,661	0.83	675,761,804	**0.95**	TM2,TM4	0.82	0.71
	LAI	661	0.55	504,661	0.94	589,675,904	**0.92**	TM2,TM4	0.79	0.70
5. Chickpea (14)	**WBM**	904	0.87	661,675	0.98	461,661,675	**0.99**	TM1,TM4,TM7	0.89	0.86
	DBM	946	0.94	489,932	0.98	489,918,1004	**0.99**	TM1,TM5,TM7	0.74	0.72
	LAI	675	0.85	661,675	0.96	589,661,675	**0.97**	TM1,TM4,TM7	0.80	0.78
6. Vetch (14)	**WBM**	918	0.42	661,904	0.76	661,818,889	**0.85**	TM3,TM5	0.78	0.74
	DBM	918	0.45	718,904	0.82	675,818,861	**0.95**	TM4,TM5	0.76	0.72
	LAI	918	0.40	461,904	0.72	475,489,904	0.78	TM1,TM4	0.74	0.77

Note: AA= piecewise multiple linear narrow-band (OMNBR) models were obtained using MAXR algorithm in SAS (1997a and 1997b).
BB= The model with highest R^2 between OMNBR (3 variable), narrow-band NDVI, and broad-band NDVI is shown in bold;
CC= bandwidths are 1.43 nanometers wide for each band center. Band centers in fraction were rounded off to nearest whole number (e.g., 549.86 nanometers as 550 nanometers.

Table 5. Evaluation of 8 categories of hyperspectral narrowband and multipsectral broadband vegetation indices.

Crop type	Biophysical variables	**Best 2-band** Vegetation index B2BVI		**Optimum multiple band** Vegetation index OMBVI		**NIR and red based** vegetation index NDVI		Transformed **Soil adjusted** Vegetation index TSAVI		**Atmospheric Corrected** vegetation index ACVI		**Middle infrare based** Vegetation inde MIVI	
		Broad Band-Landsat TM	Narrow Band-Hyper-spectral	Broad Band-Landsat TM	Narrow Band-Hyper-spectral	Broad Band-Landsat TM	Narrow Band-Hyper-spectral	Broad Band-Landsat TM	Narrow Band-Hyper-spectral	Broad Band-Landsat TM	Narrow Band-Hyper-spectral	Broad Band-Landsat TM	Nar Ban Hyp spe
1. Barley	WBM	0.75	**0.84**	0.68	0.80	0.75	**0.84**	0.74	**0.84**	0.75	Atmos-pheric affect NOT signifi-cant .	0.58	Mid infra data NO avai ble
	LAI	0.70	0.79	0.64	**0.82**	0.63	0.79	0.72	0.73	0.68		0.65	
2. Wheat	WBM	0.70	**0.83**	0.60	0.76	0.69	0.82	0.69	0.79	0.69		0.62	
	LAI	0.66	**0.74**	0.60	0.60	0.59	0.72	0.65	0.73	0.71		0.55	
3. Lentil	WBM	0.80	0.85	0.82	0.82	0.80	0.85	0.79	**0.86**	0.82	Atmos-pheric affect NOT signifi-cant .	0.67	Mid infra data NO avai ble
	LAI	0.78	**0.84**	0.79	**0.84**	0.78	0.84	0.77	0.83	0.79		0.66	
4. Cumin	WBM	0.75	0.80	0.77	**0.89**	0.63	0.75	0.55	0.76	0.73		0.62	
	LAI	0.70	0.85	0.79	**0.97**	0.70	0.77	0.51	0.75	0.77		0.58	
5. Chickpea	WBM	0.86	0.95	0.89	**0.99**	0.86	0.88	0.86	0.94	0.75		0.78	
	LAI	0.78	0.92	0.80	**0.97**	0.78	0.79	0.78	0.87	0.68		0.70	
6. Vetch	WBM	0.74	0.75	0.78	**0.85**	0.73	0.82	0.68	0.73	0.75		0.74	
	LAI	0.77	**0.80**	0.74	0.78	0.63	0.79	0.61	0.63	0.68		0.77	

Table 6. Hyperspectral band centers and bandwidths for optimal agricultural crop information.

Band number	Wavelength portion name	Band center: λ (nanometers)	Band Width: Δλ (nanometers)	Band description or significance
1	**Blue**	490	30	Crop to soil reflectance ratio minima for blue and green bands. Sensitive to loss of chlorophyll, browning, ripening, senescing, and soil background effects (Thenkabail et al.1999). Very sensitive to senescing rates and is generally an excellent predictor of grain yield. Also sensitive to carotenoid pigments (Blackburn, 1998; Tucker, 1977). Blue range use is, however, questionable due to atmospheric effects and small contrast in reflectance of soil and vegetation (anonymous reviewer).
2	**Green 1**	520	15	Positive change in reflectance per unit change in wavelength of this visible spectrum is maximum around this "green" waveband. First order derivative plot of crop spectra will show this (e.g., Thenkabail et al. 1999, Elvidge and Chen, 1995). Nichol et al. (2000) found this band to be sensitive to pigment content.
3	**Green 2**	550	25	Green band peak (or the point maximal reflectance) in the visible spectrum. Is strongly related to total clhorophyll (Schepers et al. 1996).
4	**Green 3**	575	15	Negative change in reflectance per unit change in wavelength of the visible spectrum is maximum around this "green" wavelength. First order derivative plot of crop spectra will show this (e.g., Thenkabail et al. 1999, Elvidge and Chen, 1995). Sensitive to pigment content (Nichol et al. 2000).
5	**Red 1**	660	20	Chlorophyll absorption pre-maxima (or reflectance minima 1). Absorption in the RED band (600-700 nm) varies significantly due to changes in factors such as biomass, LAI, soil background, cultivar types, canopy structure, nitrogen, moisture, and stress in plants (Elvidge and Chen, 1995; Carter, 1997; Blackburn, 1998).
6	**Red 2**	675	15	Chloropyll absorption maxima anywhere in 350 to 1050 nm range of the spectrum (or reflectance minima). Greatest crop-soil contrast is around this band center for most crops in most growing conditions (Thenkabail et al. 2000). Strong correlations with Chlorophyll a and chlorophyll b (Blackburn 1998 and 1999).
7	**Red-edge 1**	700	5	Chlorophyll absorption post-maxima (or reflectance minima 2). This is a point of sudden change in reflectance from near-maximal red absorption to beginning of the most dramatic increase in reflectance along the red-edge. Found most sensitive to plant stress and was found the most sensitive RED band by Carter (1994).
8	**Red-edge 2**	720	15	Critical point on the red-edge around which there is maximum change in the slope of the reflectance spectra per unit change in wavelength anywhere in the 350 to 1050 nm. First order derivative plot of crop spectra will show this (e.g., Thenkabail et al. 1999, Elvidge and Chen, 1995). Sensitive to temporal variations in crop growth and condition resulting in red-edge shifts. Sensitive to vegetation stress and provides additional information about chlorophyll and nitrogen status of plants (Clevers, 1999, Shaw et al. 1998, Elvidge and Chen, 1995).
9	**NIR**	845	120	Center of "NIR shoulder". For many crops, a broad-band or a narrow-band will provide the same result due to near uniform reflectance throughout the NIR shoulder. In such instances, other bands along the NIR shoulder will be redundant due to similar information as this waveband. Strong correlation with total clhorophyll (Schepers et al. 1996).
10	**NIR peak 1**	905	15	Peak or maximum reflectance region of the NIR spectrum for certain types and/or growth stages of vegetation or crops. Crops such as cotton and corn or when crops are under stress or senescing there is significant change in reflectance along the "NIR shoulder" (740-940 nm) (Thenkabail et al. 2000, Thenkabail et al. 1999). Useful for computing crop moisture sensitive index (Penuelas et al. 1993).
11	**NIR peak 2**	920	15	Peak or maximum reflectance region of the NIR spectrum for certain other types and/or growth stages of vegetation or crops. Crops such as cotton and corn or when crops are under stress or senescing there is significant change in reflectance along the "NIR shoulder" (740-940 nm) (Thenkabail et al. 2000, Thenkabail et al. 1999).
12	**NIR-Moisture sensitive**	975	10	Center of the moisture sensitive "trough" portion of NIR. The "trough" portion varies in 940 to 1040 nm and typically has minimum reflectance around 975 nm (or point of maximum "dip" in the trough portion). Plant moisture sensitive band (Peñuelas et al. 1995, Thenkabail et. al. 2000). Direct measurements of water vapour in and over vegetation canopies is feasible (Richey et al. 1989).